ARTICLE IN PRESS

Environmental Research ∎ (∎∎∎∎) ∎∎∎–∎∎∎

Contents lists available at SciVerse ScienceDirect

Environmental Research

journal homepage: www.elsevier.com/locate/envres

Race, socioeconomic status, and air pollution exposure in North Carolina

Simone C. Gray [a,*], Sharon E. Edwards [a], Marie Lynn Miranda [a,b]

[a] Children's Environmental Health Initiative, School of Natural Resources and Environment, University of Michigan, Ann Arbor, MI, USA
[b] Department of Pediatrics, University of Michigan, Ann Arbor, MI, USA

ARTICLE INFO

Article history:
Received 19 November 2012
Received in revised form
7 March 2013
Accepted 13 June 2013

Keywords:
Air pollution
Data fusion
Environmental justice
Exposure predictions
Socioeconomic status

ABSTRACT

Background: Although studies suggest that exposure to pollutants is associated with race/ethnicity and socio-economic status (SES), many studies are limited to the geographic regions where monitoring stations are located.

Objectives: This study uses modeled predictive surfaces to examine the relationship between air pollution exposure, race/ethnicity, and measures of SES across the entire State of North Carolina.

Methods: The daily predictions of particulate matter $<2.5\ \mu m$ in aerodynamic diameter ($PM_{2.5}$) and ozone (O_3) were determined using a spatial model that fused data from two sources: point air monitoring data and gridded numerical output. These daily predicted pollution levels for 2002 were linked with Census data. We examine the relationship between the census-tract level predicted concentration measures, SES, and racial composition.

Results: SES and race/ethnicity were related to predicted concentrations of both $PM_{2.5}$ and O_3 for census tracts in North Carolina. Lower SES and higher proportion minority population were associated with higher levels of $PM_{2.5}$. An interquartile range (IQR) increase of median household income reduced the predicted average $PM_{2.5}$ level by 0.10 $\mu g/m^3$. The opposite relationship was true for O_3. An IQR increase of median household income increased the predicted average O_3 measure by 0.11 ppb.

Conclusions: The analyses demonstrate that SES and race/ethnicity are related to predicted estimates of $PM_{2.5}$ and O_3 for census tracts in North Carolina. These findings offer a baseline for future exposure modeling work involving SES and air pollution for the entire state and not just among the populations residing near monitoring networks.

1. Introduction

The United States Environmental Protection Agency (USEPA) defines environmental justice (EJ) as the “fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies” (USEPA, 2010). Disadvantaged populations are at increased risk for diabetes (Karter et al., 2002), cancer, infant mortality, and a myriad of other diseases (Institute of Medicine, 1999), and an increased burden of exposure to environmental stressors may exacerbate health disparities. The Institute of Medicine acknowledges that environmental risk factors are viewed as an additional health burden to these higher risk groups (1999). In an attempt to strengthen EJ efforts, the USEPA recently developed Plan EJ 2014, the USEPA (2011) strategy for addressing EJ issues and protecting human health and the environment in overburdened communities.

Over the past 12 years, much of the research surrounding EJ has hinged on the concern that poor or minority groups may be at an increased risk from exposure to environmental stressors (Downey, 2007; NEJAC, 2004; Ringquist, 2005; Stretesky and Hogan, 1998). A large body of research has shown that disparities exist in the distribution of exposure to environmental pollutants and hazards across race and income levels (Kramer et al., 2000; Mennis and Jordan, 2005; Morello-Frosch et al., 2002; Pastor et al., 2004; Perlin et al., 1999; Williams and Collins, 2001). When narrowing the EJ research to air pollutants, studies have been conducted across the US in Arizona (Grineski et al., 2007), California (Marshall, 2008) and several states in the Northeastern U.S. (Brochu et al., 2011; Gwynn and George, 2001; Yanosky et al.,

Abbreviations: AQS, Air Quality System; CMAQ, Community Multi-Scale Air Quality Model; EJ, Environmental justice; NDI, Neighborhood deprivation index; NHB, Non-Hispanic black; O_3, Ozone; PM2.5, Particulate matter $<2.5\ \mu m$ in aerodynamic diameter; SES, Socio-economic status; SHEDS, Stochastic human exposure and dose simulation; USEPA, US Environmental Protection Agency.

* Correspondence to: Centers for Disease Control and Prevention, Quantitative Sciences and Data Management Branch, 1600 Clifton Rd NE, Mailstop E-48, Atlanta, GA 30333. Fax: +1 404 639 8642.
E-mail addresses: simonegray@cdc.gov (S.C. Gray), seedward@umich.edu (S.E. Edwards), mlmirand@umich.edu (M.L. Miranda).

0013-9351/$ - see front matter Published by Elsevier Inc.
http://dx.doi.org/10.1016/j.envres.2013.06.005

2008). Few studies have focused on areas where air pollution levels are typically below federal standards, such as North Carolina.

Studies have shown that exposure to air pollution may elevate the risk of adverse health outcomes, including mortality (Bell et al., 2004; Dockery et al., 1993; Pope et al., 2002, 2004; Schwartz, 1994), cardiovascular and respiratory morbidity (Dominici et al., 2006; Peters et al., 2004; Tonne et al., 2007), and pregnancy outcomes (Bell et al., 2007; Gray et al., 2010; Pope and Dockery, 2006; Pope et al., 1995; Schulz et al., 2005). These health effects have been attributed to both short term and long term exposure to pollutants such as air borne particulate matter and ozone (Brunekreef and Holgate, 2002). As detrimental as environmental stressors are to human health, it is important to note that exposure to air pollution may not affect all individuals in a population the same way or even at the same rate (Bell and Dominici, 2008; Brunekreef and Holgate, 2002; Currie et al., 2009; Woodruff et al., 1997). Environmental pollutants can have a disparate effect among economically disadvantaged and minority populations (Sexton et al., 1993), groups that are also more likely to live in areas with higher levels of pollution, thus potentially detracting from their health (Gwynn and George, 2001; Perlin et al., 2001; Woodruff et al., 2003; Yanosky et al., 2008).

It is difficult to obtain an exact measure of personal air pollution exposure for assessing disparities. Health and EJ studies often use measurements obtained from monitoring stations as surrogates for individual exposure (Sram et al., 2005). There are many limitations to using measurements from monitored data. The collected measurements often have missing data as estimates are not always recorded every day. Additionally, the sparse network of monitoring stations misses large geographic regions and limits the population that can be assessed. Alternatively, proximity to major roadways has also been used as a metric for individual exposures due to the large contribution of traffic emissions to ambient air pollution (Hart et al., 2009; Karr et al., 2009; Miranda et al., 2012). Other studies have explored the use of modeling techniques for estimating exposure concentration measurements including the Community Multi-Scale Air Quality Model (CMAQ), the probabilistic NAAQS Exposure Model (pCNEM) and the stochastic human exposure and dose simulation (SHEDS-PM) (Berrocal et al., 2010b; Zidek et al., 2003, 2007).

In this study, we explore racial and socioeconomic disparities in exposure to air pollution across the State of North Carolina. Unlike previous studies of EJ dimensions of air pollution, which limit analysis of populations living near air quality monitoring stations, we use predictive surfaces of ozone (O_3) and particulate matter-$<2.5\ \mu m$ in aerodynamic diameter ($PM_{2.5}$) at the census-tract level covering all of North Carolina. This analysis seeks to provide a better understanding of the EJ dimension of air pollution exposure across the entire North Carolina population.

2. Methods

2.1. Exposure data

Daily fused predictions surfaces of $PM_{2.5}$ (daily average in $\mu g/m^3$) and O_3 (daily 8-h maximum in ppb) were obtained from the USEPA for 2002 (www.epa.gov/esd/land-sci/lcb/lcb_faqsd.html). A Bayesian space-time "downscaling" fusion modeling approach was used to develop these predictive surfaces (Berrocal et al., 2010a). The downscaling fusion model uses input data from two sources: point monitoring data and numerical model gridded output. The air quality monitoring data came from the Environmental Protection Agency Air Quality System (AQS) repository database, and the numerical output came from the Models-3/Community Multiscale Air Quality (CMAQ; http://www.epa.gov/asmdnerl/CMAQ) model run at the 12-km spatial resolution. An evaluation of the CMAQ model reveals overall agreement with the AQS network but with biased estimates (Mebust et al., 2003). The fused model combines the two data sources to attempt to adjust for the existing bias in the CMAQ model and produces predictions for census tract centroids across the entire State of North Carolina (Byun and Schere, 2006).

The term "downscaler" is used because adaptive smoothing of the areal CMAQ output is scaled to the point-level air monitoring data. The downscaler relates CMAQ output and air quality data using a spatial linear regression with bias coefficients (additive and multiplicative) that can vary in space and time. This approach to fusion modeling provides a new answer to the "change-of-support" problem where we would like to predict air pollution at a certain spatial resolution, but must reconcile the difference between point monitoring data and areal CMAQ output (Berrocal et al., 2010a, 2012). The fused output has complete spatial coverage of the study area at the census tract level. Further details and descriptions of the modeling technique and predictive performance can be found in Berrocal et al. (2012).

2.2. Demographic data

Measures of racial composition and socio-economic status (SES) for the general population of North Carolina were obtained from the 2000 US Census at the census tract level for the 1563 populated census tracts in the state (http://factfinder2.census.gov). The size of census tracts in North Carolina ranges from 0.4 to 3529.6 km^2 with a mean of 87.8 km^2 and a standard deviation (SD) of 171.3. Population density ranged from 2 to 4380 people per sq km with a mean of 442 people per sq km and SD of 550. Fig. 1 shows the 2000 population density for the State of North Carolina. SES variables obtained from the census included measures of poverty (percentage of census tract population below the poverty line), educational attainment (percentage of persons with less than a high school education) and measures of income (median household income). Racial composition for each census tracts was based on the tract percentage of those who self-reported as non-Hispanic black (NHB) and Hispanic. These variables were chosen based on associations between air pollution, race/ethnicity, and SES in previous studies (Miranda et al., 2011; Yanosky et al., 2008).

Table 1 shows the correlations between the SES and race/ethnicity variables. As expected, tract-level median household income was negatively correlated with both percent in poverty and percent less than high school education, with $r\sim-0.7$ in both cases. Percent in poverty was positively correlated with percent less than HS education and percent NHB, $r=0.61$ and 0.64, respectively. Correlations were significant in all cases ($p<0.0001$). We also included a neighborhood deprivation index (NDI) as a census level summary for living in a deprived neighborhood. The NDI was constructed as an aggregated measure of SES for North Carolina following the methodology described in Messer et al. (2006) and incorporates census SES variables. Using principal components analysis, the NDI was created as a standardized score having mean 0 and standard deviation of 1.

2.3. Statistical analysis

We examine the association between measures of SES, race/ethnicity, and average concentrations of O_3 and $PM_{2.5}$ at the census tract level using linear mixed regression models. We used the predicted $PM_{2.5}$ and O_3 concentrations as our outcome variables and examined the independent effect of SES, race/ethnicity on the level of each pollutant. We included a random intercept at the county level to account for unmeasured variation due to population-level characteristics. The census variables used in the models included: percent of population below the poverty line (poverty), median household income, percent of population with less than a high school (HS) level education, percent NHB, and percent Hispanic. We also included NDI as an independent covariate. We used the annual average $PM_{2.5}$ for the year 2002. For O_3 we consider both the annual average and also the average during the O_3 season for North Carolina, which is from April 1 through September 30. The model results were equivalent, and we present only those based on the O_3 season. All statistical analyses were performed using SAS 9.3 (SAS Institute, Cary NC).

3. Results

3.1. Race and SES summaries

Fig. 2 shows the spatial distribution of median household income and the percent in poverty by quintiles for census tracts in North Carolina. In the maps, darker shades are used to denote lower SES, for example lower income or higher poverty. In general, higher SES areas are located in the larger metropolitan regions of the state, while lower SES levels are clustered around the northeast and southern tracts of the state, as well as the far western Appalachian region. It is important to note that the smaller surface area of the census tracts clustered in metropolitan areas tend to mask the few tracts with lower SES characteristics. The maps of percent with less than high school education (not presented here)

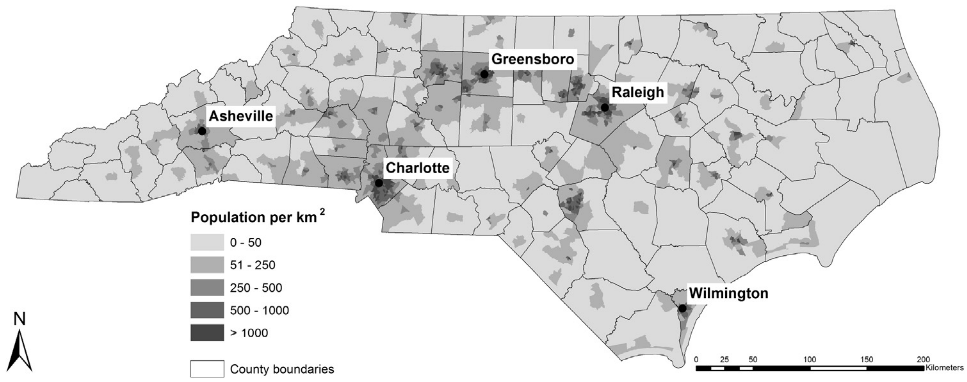

Fig. 1. Population density in 2000 for North Carolina.

Table 1
Pearson's correlation coefficients between race, ethnicity and SES measures.

	Income	Poverty	Education	% NHB	% Hispanic	NDI
Income	1					
Poverty	−0.70*	1				
Education	−0.71*	0.61*	1			
% NHB	−0.47*	0.64*	0.45*	1		
% Hispanic	−0.21*	0.22*	0.24*	0.18*	1	
NDI	−0.80*	0.88*	0.81*	0.72*	0.30*	1

* $p < 0.0001$.

revealed similar patterns as the other SES measures. Median household income ranged from $4545 to $144058, while percent in poverty and percent with less than high school education rates ranged from 0.23 to 93.23%, and 0 to 68.57%, respectively.

Fig. 3 shows the spatial distribution of percent NHB and percent Hispanic by quintiles for census tracts in North Carolina. In general, we find a cluster of tracts with large NHB populations in the northeastern part of the state and the smallest proportion NHB throughout the western mountain region of North Carolina. Percent Hispanic followed a similar pattern of low percentages through the mountain region of North Carolina, but was at the highest levels in the southeastern portion of the state.

3.2. Air pollution summaries

Fig. 4 shows the predicted average $PM_{2.5}$ and O_3 concentration levels in quintiles by census tract for North Carolina. Values of $PM_{2.5}$ ranged from 7.9 to 9.3 μg/m^3, while O_3 predictions ranged between 45.7 and 57.9 ppb. O_3 predictions displayed in the figure are the mean O_3 levels during the 2002 O_3 season. $PM_{2.5}$ levels, which are displayed as the mean $PM_{2.5}$ levels in 2002, are highest in the more populated metropolitan areas and lowest along the eastern coast and in the western mountain region. The highest O_3 levels were seen in central North Carolina and the lowest estimates along the coast. There was a weak negative correlation between the predicted averages of $PM_{2.5}$ and O_3, with $r \sim -0.09$ ($p < 0.001$).

3.3. $PM_{2.5}$. SES, and race/ethnicity

In independent models, predicted tract-level annual average $PM_{2.5}$ concentrations were significantly associated with all of the SES variables (median household income, percent in poverty, percent less than HS education, and NDI), as well as percent NHB and percent Hispanic ($p < .01$). All models indicated that lower SES, higher deprivation, and higher minority characteristics were consistently associated with slightly higher levels of annual average $PM_{2.5}$ (see Table 2). Median household income was negatively associated with average predicted $PM_{2.5}$, while percent in poverty, percent with less than HS education, NDI, percent NHB, and percent Hispanic had positive associations with $PM_{2.5}$. Table 2 shows the change in $PM_{2.5}$ and O_3 levels for an interquartile range (IQR) increase in census tract SES, NDI, and race/ethnicity measures. An IQR increase of median household income reduced the predicted average $PM_{2.5}$ level by 0.10 μg/m^3. IQR increases in percent in poverty, percent less than HS education, percent NHB, percent Hispanic, and the NDI increased $PM_{2.5}$ measures by 0.12, 0.14, 0.15, 0.04 and 0.12 μg/m^3, respectively.

3.4. O_3. SES, and race/ethnicity

As with $PM_{2.5}$, predicted tract-level average O_3 concentrations during the ozone season were significantly associated in independent models with all of the SES variables (median household income, percent in poverty, percent less than HS education, and NDI), as well as percent NHB and percent Hispanic ($p < .01$). All models revealed that lower SES, higher deprivation, and higher minority characteristics were consistently associated with slightly lower levels of average O_3 (see Table 2). The association between O_3 and all demographic variables were opposite to the findings for $PM_{2.5}$. Median household income was positively associated with average predicted in-season O_3, while percent below poverty, percent with less than HS education, NDI, percent NHB, and percent Hispanic had negative associations with O_3. An IQR increase of median household income increased the predicted average O_3 measure by 0.11 ppb. IQR increases of percent in poverty, percent less than HS education, percent NHB, percent Hispanic, and the NDI decreased O_3 levels by 0.12, 0.16, 0.15, 0.01 and 0.13 ppb, respectively.

3.5. Discussion

Understanding the relationship between race, ethnicity, and SES with environmental hazards, such as air pollution, is important for EJ efforts, as well as epidemiological research. The high correlation between these variables and many health outcomes could potentially confound or modify the results of health effects studies. Attempts to control for confounding are further limited by obtaining relevant and complete data for various risk factors. Having to rely on monitoring networks for air pollution data is a further limitation in EJ and epidemiological studies. This paper used recently developed air pollution models from the USEPA that predict $PM_{2.5}$ and O_3 levels at the census tract level for the entire State of North Carolina to examine the relationship between air pollution levels and measures of SES and minority status.

Several studies suggest that minorities and people with lower SES are exposed to disproportionately high levels of air pollution (Downey, 2003; Finkelstein et al., 2005; Jerrett et al., 2004). Ash and Fetter (2004) showed that African American and lower income populations

Please cite this article as: Gray, S.C., et al., Race, socioeconomic status, and air pollution exposure in North Carolina. Environ. Res. (2013), http://dx.doi.org/10.1016/j.envres.2013.06.005

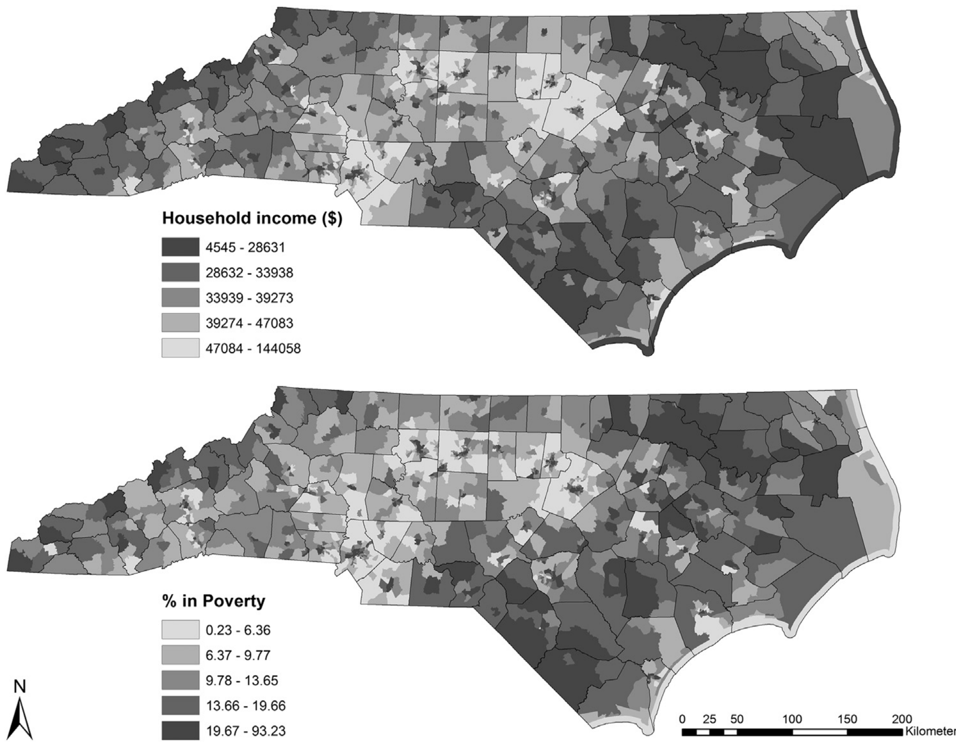

Fig. 2. Distribution of median household income and percent of population below the poverty line by census tract in North Carolina.

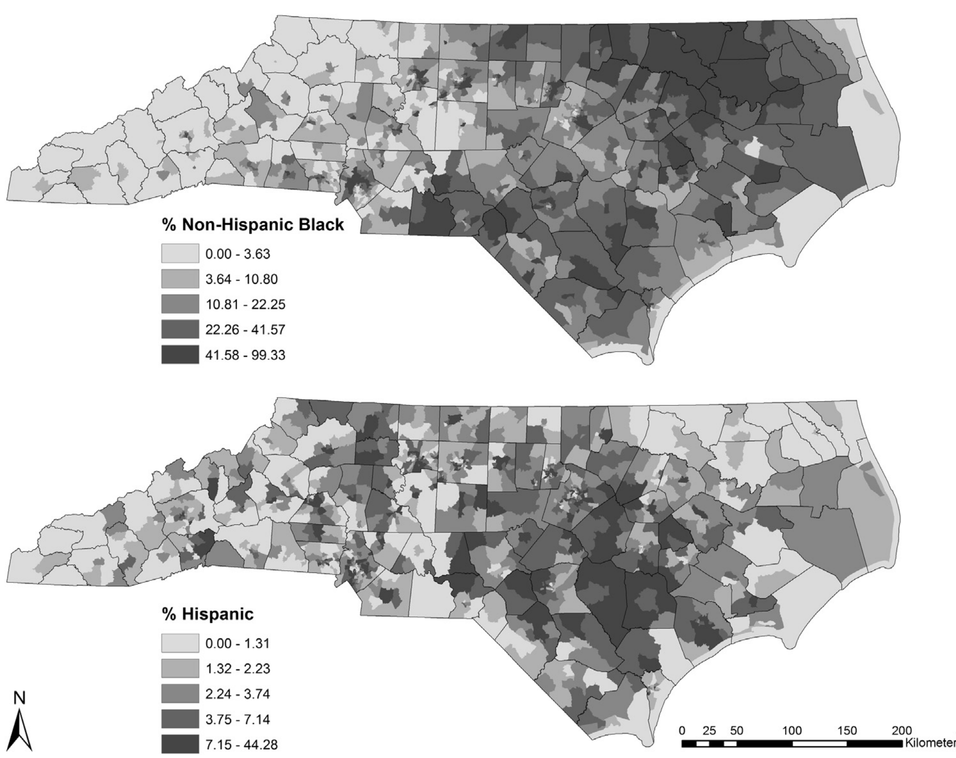

Fig. 3. Distribution of percent NHB and percent Hispanic rates by census tract in North Carolina.

tend to live in more polluted areas in a nationwide US study. Brochu et al. (2011) also showed that lower SES and African American populations are exposed to higher ambient particulate matter in the Northeastern US. While many of these studies differ in spatial scale, pollutants of interest, geographic location, and methodology implemented, the general findings show that there is a relationship between community disadvantage and increased levels of air pollution.

This study provides further evidence that disadvantaged communities experience a higher burden of air pollution. In general, this study showed that SES and race/ethnicity are in fact related to predicted estimates of both $PM_{2.5}$ and O_3 for census tracts in North Carolina. Although all associations were significant for both pollutants, they were not in the same direction. $PM_{2.5}$ was consistently and significantly higher in areas with lower SES,

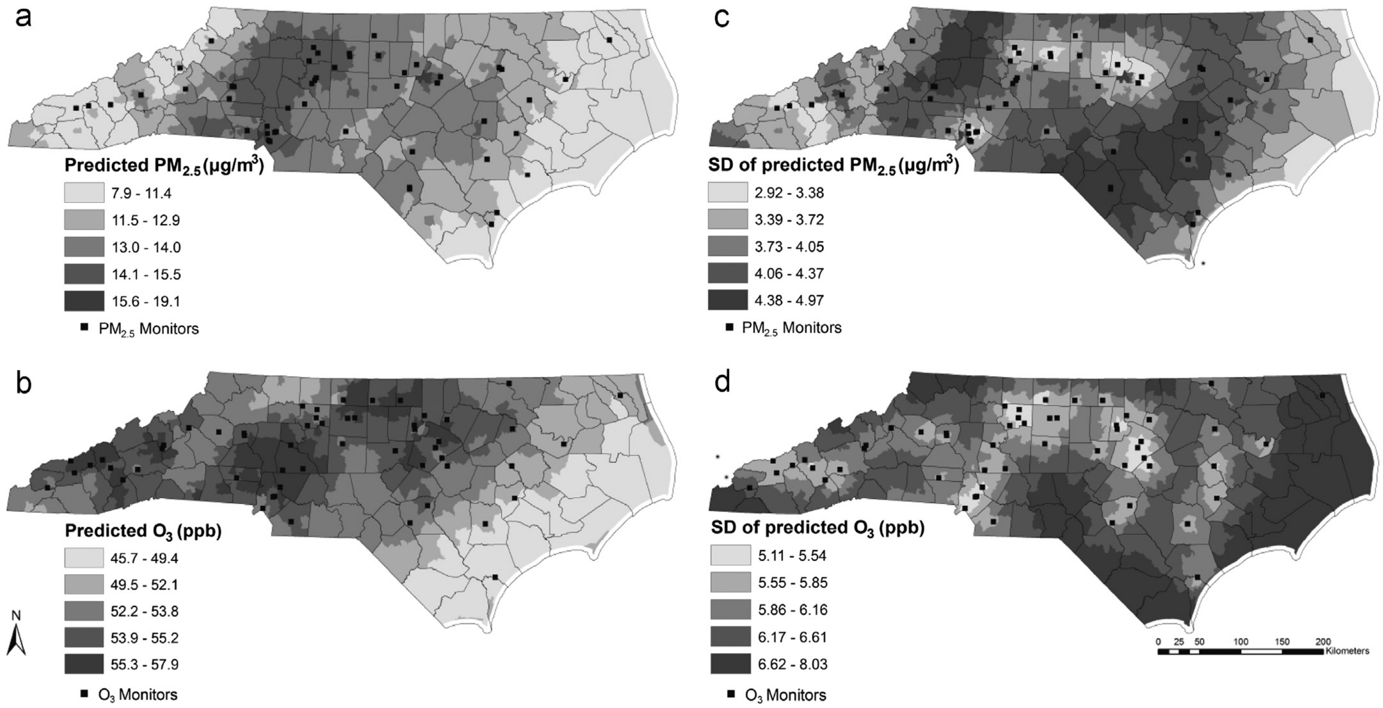

Fig. 4. Predicted mean concentrations for: (a) $PM_{2.5}$ and (b) O_3. Standard deviation of predicted concentrations for: (c) $PM_{2.5}$ and (d) O_3.

Table 2
Changes in predicted average $PM_{2.5}$ ($\mu g/m^3$) and O_3 (ppb) concentrations for an IQR increase in risk factors.

	IQR	PM2.5	O3
Income $	13877	−0.10**	0.11**
% In poverty	10.49	0.12**	−0.12**
% Less HS education	17.59	0.14**	−0.16**
% NHB	29.80	0.15**	−0.15**
% Hispanic	4.14	0.04*	−0.01*
NDI	1.08	0.12**	−0.13**

* $p < 0.01$.
** $p < 0.001$.

higher deprivation, and higher minority rates, while O_3 levels were lower in areas with lower SES, higher deprivation, and higher minority rates. The magnitude of the effects, while small and in different directions, was similar and consistent across both pollutants. The largest contributing factors to changes in both $PM_{2.5}$ and O_3 were percent with less than a high school level education and percent NHB, while percent Hispanic had the least effect. Our results showing that lower O_3 concentrations are associated with lower poverty rates are similar to the results of a national study which restricted to communities with air quality monitors (Miranda et al., 2011). Marshall (2008) also showed this comparable relationship with O_3 and lower income populations in California's South Coast Air Basin. Our results for $PM_{2.5}$ are similar in scale to the results reported by Brochu et al. (2011) in their study on the Northeastern US.

This study was limited by several factors. First, we used data from the 2000 US Census with 2002 air pollution predictions. Second, we acknowledge that concentration data is not an explicit measure of exposure, as it does not take into account daily activity patterns, occupational exposures, indoor sources of exposure, or ventilation conditions. Third, measurement error is inherent in the fused model estimates, with greater uncertainty in the areas furthest away from the monitoring stations; however, we note that in the Eastern US, the empirical coverage of the 95% predictive interval for the downscaler model is 94.9%, showing excellent predictive performance overall (Berrocal et al., 2012). Additionally, for the census tracts in North Carolina containing monitoring stations, the overall correlation between the fused output and the AQS measurements was 0.966 and 0.973 for $PM_{2.5}$ and O_3, respectively ($p < 0.0001$ for both). Fourth, the aggregated group-level associations found in this study are particular to North Carolina census tracts and cannot necessarily be translated into individual effects or other locations. Finally, using census tract data limits our ability to determine whether finer scale variability of SES and minority status is associated with air pollution.

Despite these limitations, there were several strengths to this study. We use population level demographic and air pollution data for the entire State of North Carolina. With data for such a large geographic region, we have increased statistical power compared to analyses restricting to populations with available air pollution data from the monitoring network alone. The fine spatial and temporal resolution of the air pollution data allowed us to obtain measurements for times and locations where monitoring data are not available. As seen in Fig. 4, monitoring stations are sparsely distributed throughout the state. Placement of monitoring stations tends to be closer to major cities and roadways and is determined based on regulatory purposes. Restricting the analysis to only census tracts containing these stations eliminates 96.8% of the study area. Alternatively, creating buffers of 10 km around a monitoring station covers 41 and 29% of the census tracts in the entire state for $PM_{2.5}$ and O_3, respectively. Increasing the buffer size to 20 km increases coverage of the state to 63% for $PM_{2.5}$ and 60% for O_3. While larger buffers around monitoring stations cover more of the study area's population, the assignment of monitored value to more distant populations becomes increasingly less reliable as buffer size increases. Additionally, although previous work has characterized differences in air pollution exposure across sub-populations, using the fused air pollution predictions rather than monitoring data alone allowed us to better understand and more deeply explore these differences by working at the population level rather than with a non-randomly restricted subset of the population.

Several independent measures of SES have been used in previous studies, including income, employment, education, living conditions, and crime. It is unclear whether environmental hazards are associated

Please cite this article as: Gray, S.C., et al., Race, socioeconomic status, and air pollution exposure in North Carolina. Environ. Res. (2013), http://dx.doi.org/10.1016/j.envres.2013.06.005

with individual or composite measures of SES. We attempt to better understand this relationship in the case of air pollution exposure by considering the association between both characterizations of individual facets of SES and a characterization that combines individual facets into a composite measure of SES, the NDI. It is important to note that the generalized areal measures of SES do not take into account individual level behavior.

Disproportionate exposure to air pollution and other environmental risks by race/ethnicity and SES has important implications for health and EJ. When disadvantaged communities bear an undue burden of toxic exposures, health disparities already adversely affecting these communities may be exacerbated. This study provides population-level evidence of disparate exposures to particulate matter in a state with relatively low levels of air pollution. These findings may support community advocacy and policy decisions aimed at issues of EJ. Such disparities are also an important public health concern, especially as we begin to explore and understand the social context of environmental exposures and how the two combined may affect health outcomes. Disparities in air pollution exposure, such as those highlighted in this paper, are thus important. Future work should further examine the relationship between SES, race/ethnicity, and air pollution at the population level in other states, particularly those with higher pollution levels than North Carolina, where EJ concerns may be even greater.

Funding sources

This work was supported by funding from the US environmental Protection Agency (RD-83329301-0).

Acknowledgments

We thank Claire Osgood for helpful data management support and Ben Strauss for assistance with the graphics presented. Dave Holland of the USEPA provided invaluable assistance with the atmospheric models used in the analysis.

The contents of this journal are solely the responsibility of the authors and do not necessarily represent the official views of the US Environmental Protection Agency.

References

Ash, M., Fetter, T.R., 2004. Who lives on the wrong side of the environmental tracks? Evidence from the EPA's risk-screening environmental indicators model. Soc. Sci. Quart. 85, 441–462.
Bell, M.L., Dominici, F., 2008. Effect modification by community characteristics on the short-term effects of ozone exposure and mortality in 98 US communities. Am. J. Epidemiol. 167, 986–997.
Bell, M.L., et al., 2007. Ambient air pollution and low birth weight in Connecticut and Massachusetts. Environ. Health Perspect. 115, 1118–1124.
Bell, M.L., et al., 2004. Ozone and short-term mortality in 95 US Urban Communities, 1987–2000. JAMA 292, 2372–2378.
Berrocal, V.J., et al., 2010a. A spatio-temporal downsscaler for output from numerical models. JABES 15, 176–197.
Berrocal, V.J., et al., 2012. Space-time data fusion under error in computer model output: an application to modeling air quality. Biometrics 68, 837–848.
Berrocal, V.J., et al., 2010b. On the use of a $PM_{2.5}$ exposure simulator to explain birthweight. Environmetrics 22, 553–571.
Brochu, P.J., et al., 2011. Particulate air pollution and socioeconomic position in rural and urban areas of the Northeastern United States. Am. J. Public Health 101, S224–S230.
Brunekreef, B., Holgate, S.T., 2002. Air pollution and health. Lancet 360, 1233–1242.
Byun, D., Schere, K.L., 2006. Review of the governing equations, computational algorithms and other components of the Models-3 Community Multiscale Air Quality (CMAQ) modeling system. Appl. Mech. Rev. 59, 51–77.
Currie, J., et al., 2009. Air pollution and infant health: lessons from New Jersey. J. Health Econ. 28, 688–703.
Dockery, D.W., et al., 1993. An association between air pollution and mortality in six U.S. cities. N. Engl. J. Med. 329, 1754–1759.
Dominici, F., et al., 2006. Fine particulate air pollution and hospital admission for cardiovascular and respiratory diseases. JAMA 295, 1127–1134.
Downey, L., 2003. Spatial measurement, geography, and urban racial inequality. Soc. Forces 81, 937–952.
Downey, L., 2007. US metropolitan-area variation in environmental inequality outcomes. Urban Stud. 44, 953–977.
Finkelstein, M.M., et al., 2005. Environmental inequality and circulatory disease mortality gradients. J. Epidemiol. Community Health 59, 481–487.
Gray, S.C., et al., 2010. Assessing exposure metrics for PM and birth weight models. J. Expo. Sci. Environ. Epidemiol. 20, 469–477.
Grineski, S., et al., 2007. Criteria air pollution and marginalized populations: environmental inequity in Metropolitan Pheonix, Arizona. Soc. Sci. Quart. 88, 535–554.
Gwynn, R.T., George, 2001. The burden of air pollution: impacts among racial minorities. Environ. Health Perspect. 109, 501–506.
Hart, J.E., et al., 2009. Exposure to traffic pollution and increased risk of rheumatoid arthritis. Environ. Health Perspect. 117, 1065–1069.
Institute of Medicine, 1999. Towards Environmental Justice: Research, Education and Health Policy Needs. National Academy Press, Washington, DC.
Jerrett, M., et al., 2004. Do socioeconomic characteristics modify short term associations between air pollution and mortailty? Evidence from a zonal time series in Hamilton, Canada. J. Epidemiol. Community Health 58, 31–40.
Karr, C.J., et al., 2009. Infant exposure to fine particulate matter and traffic and risk of hospitalization for RSV bronchiolitis in a region with lower ambient air pollution. Environ. Res. 109, 321–327.
Karter, A.J., et al., 2002. Ethnic disparities in diabetic complications in an insured population. JAMA 287, 2519–2527.
Kramer, M.S., et al., 2000. Socio-economic disparities in pregnancy outcomes: why do the poor fare so poorly? Paediatr. Perinat. Epidemiol. 14, 194–210.
Marshall, J.D., 2008. Environmental inequality: airpollution exposures in California's south coast air basin. Atmos. Environ. 42, 5499–5503.
Mebust, M.R., et al., 2003. Models-3 Community Multiscale Air Quality (CMAQ) model aerosol component 2. Model evaluation. J. Geophys. Res. 108, 4184–4202.
Mennis, J.L., Jordan, L., 2005. The distribution of environmental equity: exploring spatial nonstationarity in multivariate models of air toxic releases. Ann. Assoc. Am. Geogr. 95, 249–268.
Messer, L.C., et al., 2006. The development of a standardized neighbourhood deprivation index. J. Urban Health 83, 1041–1062.
Miranda, M.L., et al., 2012. Proximity to roadways and pregnancy outcomes. J. Expo. Sci. Environ. Epidemiol., 1–7.
Miranda, M.L., et al., 2011. Making the environmental justice grade: the relative burden of air pollution exposure in the United States. Int. J. Environ. Res. Public Health. 8, 1755–1771.
Morello-Frosch, R.A., et al., 2002. Environmental justice and regional inequality in Southern California: implications for future research. Environ. Health Perspect. 110, 149–153.
NEJAC Ensuring Risk Reduction in Communities with Multiple Environmental Stressors: Environmental Justice and Cumulative Risks/Impacts. 2004.
Pastor, M., et al., 2004. Reading, writing, and toxics: children's health, academic performance, and environmental justice in Los Angeles. Environ. Plann. C 22, 271–290.
Perlin, S., et al., 1999. Distribution of industrial air emissions by income and race in the United States: an approach using the Toxics Release Inventory. Environ. Sci. Technol. 29, 69–80.
Perlin, S., et al., 2001. Residential proximity to industrial sources of air pollution: interrelationships among race, poverty, and age. J. Air Waste Manage. Assoc. 51, 406–421.
Peters, A., et al., 2004. Exposure to traffice and the onset of myocardial infarction. N. Engl. J. Med. 351, 1721–1730.
Pope III, C.A., et al., 2002. Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. JAMA 287, 1132–1141.
Pope III, C.A., et al., 2004. Cardiovascular mortality and long-term exposure to particulate air pollution: epidemiological evidence of general pathophysiological pathways of disease. Circulation 109, 71–77.
Pope III, C.A., Dockery, D.W., 2006. Health effects of fine particulate air pollution: lines that connect. J Air Waste Manage Assoc 56, 709–742.
Pope III, C.A., et al., 1995. Review of epidemiological evidence of health effects of particulate air pollution. Inhalation Toxicol. 7, 1–18.
Ringquist, E.J., 2005. Assessing evidence of environmental inequities: a meta-analysis. J. Policy Anal. Manag. 24, 223–247.
Schulz, A.J., et al., 2005. Social and physical environments and disparities in risk for cardiovascular disease: the healthy environments partnership conceptual model. Environ. Health Perspect. 113, 1817–1825.
Schwartz, J., 1994. Air pollution and daily mortality: a review and meta analysis. Environ. Res. 64, 36–52.
Sexton, K., et al., 1993. Air pollution health risks: do class and race matter? Toxicol. Ind. Health 9, 843–878.
Sram, R.J., et al., 2005. Ambient air pollution and pregnancy outcomes: a review of the literature. Environ. Health Persect. 113, 375–382.
Stretesky, P., Hogan, M.J., 1998. Environmental justice: an analysis of superfund sites in Florida. Soc. Probl. 45, 268–287.
Tonne, C., et al., 2007. A case-control analysis of exposure to traffic and acute myocardial infarction. Environ. Health Persect. 115, 53–57.
USEPA ⟨http://www.epa.gov/environmentaljustice/basics/index.html⟩. 2010.
USEPA Plan EJ 2014. Office of Environmental Justice, Washington, DC, 2011.
Williams, D.R., Collins, C., 2001. Racial residential segregation: a fundamental cause of racial disparities in health. Public Health Rep. 16, 404–416.

Woodruff, T.J., et al., 1997. The relationship between selected causes of postneonatal infant mortality and particulate air pollution in the United States. Environ. Health Perspect. 105, 608–612.
Woodruff, T.J., et al., 2003. Disparities in exposure to air pollution during pregnancy. Environ. Health Perspect. 111, 942–946.
Yanosky, J.D., et al., 2008. Associations between measures of socioeconomic position and chronic nitrogen dioxide exposure in Worcester, Massachusetts. J. Toxicol. Environ. Health Part A 71, 1593–1602.
Zidek, J.V., et al., A Computational Model for Estimating Personal Exposure to Air Pollutants with Application to London's PM_{10} in 1997. Technical Report of the Statistical and Applied Mathematical Sciences Institute, 2003.
Zidek, J.V., et al., 2007. A framework for predicting personal exposures to environmental hazards. Environ. Ecol. Stat. 01, 411–431.